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# FEATURE-DOMAIN SUPER-RESOLUTION FOR IRIS RECOGNITION

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## ABSTRACT

Uncooperative iris identification systems at a distance suffer from poor resolution of the captured iris images, which significantly degrades iris recognition performance. Super-resolution techniques have been employed to enhance the resolution of iris images and improve the recognition performance. However, all existing super-resolution approaches proposed for the iris biometric super-resolve pixel intensity values. This paper considers transferring super-resolution of iris images from the intensity domain to the feature domain. By directly super-resolving only the features essential for recognition, and by incorporating domain specific information from iris models, improved recognition performance compared to pixel domain super-resolution can be achieved. This is the first paper to investigate the possibility of feature-domain super-resolution for iris recognition, and experiments confirm the validity of the proposed approach.

**Index Terms**— iris recognition, iris recognition at a distance, super-resolution, feature-domain super-resolution

## 1. INTRODUCTION

Biometrics are reliable methods for automatic identification of individuals based on their physiological and behavioural characteristics. Among the biometrics, iris has been shown to be one of the most accurate traits for human identification due to its stability and high degree of freedom in texture [1]. Because of existing close-distance constraints between an iris and a capturing camera, the research community is interested in enabling iris recognition to be conducted in less constrained environments, such as at a distance. The most challenging problem with uncooperative iris identification at a distance is the lack of pixel resolution. In [2], a significant recognition performance degradation has been demonstrated when the iris image resolution decreases.

Super-resolution techniques have previously been employed to address the low resolution problems for a number of applications [3]. These techniques reconstruct or learn lost high-frequency information to enhance the resolution of an imaging system. Recently, these techniques have been effectively exploited to enhance resolution, and mainly to improve

recognition performance of biometric systems, including face [4] and iris [5–7].

Traditional super-resolution approaches use the intensity values of pixels to perform pixel-domain super-resolution. However, these pixel-domain approaches pose two questions:

- The aim of applying super-resolution to biometrics is not for visual enhancement, but to improve recognition performance. Most existing super-resolution approaches are designed to produce a visual enhancement. *If recognition improvement is desired, why do we not focus on super-resolving only items essential for recognition?*
- Each biometric modality has its own characteristics. Most existing super-resolution approaches for biometrics are general-scene super-resolution approaches. *Can any specific information from biometric models be exploited to improve super-resolution performance?*

Recently, Gunturk et al. [8] proposed a feature-domain super-resolution approach, which super-resolves face images in the eigenface domain, rather than the pixel domain. The difference between a feature-domain super-resolution and a pixel-domain super-resolution approach for biometric recognition is illustrated in Figure 1. This super-resolution approach in the face feature domain has been shown to: (1) no longer try to obtain a visually improved high-resolution image, but to improve recognition performance instead, (2) reconstruct only essential features required by the recognition system directly in feature domain, (3) exhibit robustness to registration errors and noise with the addition of model-based constraints, (4) outperform other pixel-domain super-resolution approaches for faces.

To further improve the performance of iris recognition systems at a distance, we seek to investigate the possibility of performing feature-based super-resolution for iris recognition. Principal Component Analysis (or Eigeniris) features of multiple low-resolution normalised iris images are extracted, then super-resolved to produce a high-resolution feature vector. The estimation problem is resolved using Bayesian statistics. Specific information relating to iris models is incorporated to constrain the estimation. The proposed feature-domain super-resolution approach is shown to outper-

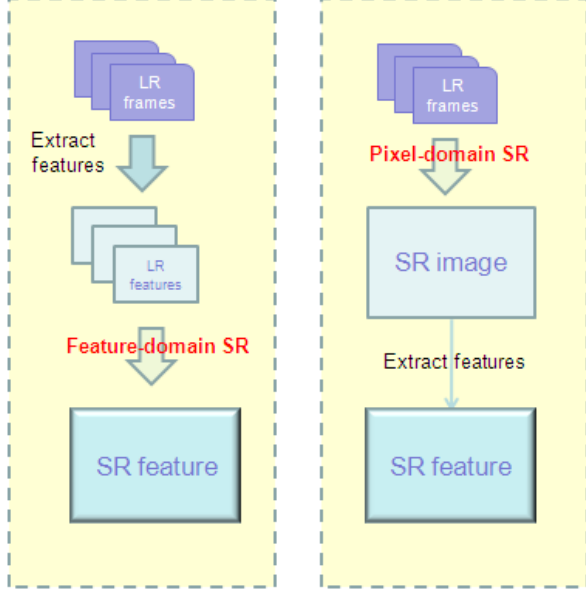


Fig. 1. Feature-domain SR vs. Pixel-domain SR.

form other pixel-domain super-resolution approaches.

The remainder of this paper is organized as follows: eigeniris recognition is briefly summarised in Section 2; Section 3 describes a feature-domain super-resolution approach for iris images; Section 4 explains our experiments and results; and the paper is concluded in Section 5.

## 2. EIGENIRIS RECOGNITION

Here we briefly introduce Principal Components Analysis (PCA), or eigeniris recognition (more details can be found in [9]). PCA is a mathematical procedure that applies an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of uncorrelated variables called principal components. Each observation (iris image) is represented as a linear combination of orthonormal vectors, called eigenvectors (eigenirises). Let  $I_1, I_2, \dots, I_K$  be the normalised and preprocessed training iris images indexed in accordance with iris class. The eigenirises are the eigenvectors of the covariance matrix  $C = \sum_{i=1}^K I_i I_i^T$ .

During the training phase, eigeniris space is estimated from gallery images. In practice, the smallest eigenvalues of  $C$  are disregarded, and an eigeniris space matrix,  $\phi$ , which contains the eigenirises as its column is formed. Thus the new transformed space has smaller dimensionality than the original space. Depending on the compromise between representation accuracy and compactness, the number of eigenirises employed can be varied.

In the testing/recognition phase, a normalised iris image,  $x$ , can be projected onto the eigeniris space as follows:  $x = \phi a + e_x$ , where  $\phi$  is the eigeniris space matrix,  $e_x$  is the rep-

resentation error,  $a$  is the eigenvalue which serves as a feature vector for representing the normalised iris image. The identity of the probe image will be estimated as the identity of the class whose feature vector has the smallest distance to the probe feature vector. The distance between two feature vectors can be determined using either Euclidean or Hamming distance.

## 3. FEATURE-DOMAIN SUPER-RESOLUTION FOR IRIS RECOGNITION

Inspired by the eigenface-domain super-resolution for face recognition by Gunturk et al. [8], we propose a five-stage feature-domain super-resolution approach for iris recognition. The first stage involves determining the relationship between low-resolution (LR) and high-resolution (HR) images in the spatial domain as is conventional [3]. Since we only focus on super-resolving features essential for recognition performance, this relationship is transformed to the relationship between LR and HR features, as shown in Stage 2. The HR features can be estimated using Bayes maximum a posteriori probability estimation (Stage 3). To solve this estimation, specific iris model constraints are incorporated into the problem (Stage 4). With the added information, the estimation problem is paraphrased and the HR features are estimated by iterative steepest decent (Stage 5). The remainder of this section explains these steps in more detail.

### Stage 1: Observation model in the spatial domain

Let  $x$  be the original HR iris image, and  $y^{(i)}$  be the  $i^{th}$  observed LR iris image after being degraded by downsampling,  $D^{(i)}$ ; blurring,  $B^{(i)}$ ; and warping,  $W^{(i)}$ . The relation between  $x, y^{(i)}$  is described as follows,

$$y^{(i)} = H^{(i)} x + n^{(i)} = D^{(i)} B^{(i)} W^{(i)} x + n^{(i)}, \quad (1)$$

where  $n^{(i)}$  is the observation noise.

### Stage 2: Observation model in the feature domain

We seek to transform the observation model from the spatial domain to the feature domain. In eigeniris recognition, HR irises,  $x$ , and observed LR irises,  $y^{(i)}$ , are represented as a superposition of eigenirises as follows,

$$x = \Phi a + e_x, \quad (2)$$

$$y^{(i)} = \Psi \hat{a}^{(i)} + e_y, \quad (3)$$

where  $\Phi, \Psi$  are eigeniris matrixes,  $a, \hat{a}^{(i)}$  are feature vectors of HR and LR iris images,  $e_x, e_y$  are representation errors.

Replacing HR and LR feature representation (2),(3) into the spatial observation model (1), we have,

$$\hat{a}^{(i)} = \Psi^T H^{(i)} \Phi a + \Psi^T H^{(i)} e_x + \Psi^T n^{(i)}. \quad (4)$$

Equation (4) shows the relationship between HR and observed LR iris features. The next sections will discuss a solution to estimate the HR iris features from this equation.

### Stage 3: Estimating HR feature problem

In Bayes statistics, a maximum a posteriori probability estimate can be used to estimate an unobserved quantity on the basis of empirical data. Using Bayes maximum a posteriori probability estimator, a HR feature can be estimated as,

$$\tilde{a} = \operatorname{argmax}_a p(\hat{a}^{(1)}, \dots, \hat{a}^{(M)} | a) p(a).$$

The estimated HR feature,  $\tilde{a}$ , is the value that maximises the product of the conditional probability  $p(\hat{a}^{(1)}, \dots, \hat{a}^{(M)} | a)$  and the priori probability  $p(a)$ .

### Stage 4: Incorporating iris model information

To solve the above estimation problem, specific information relating to iris models can be incorporated in the form of two assumptions:

1. Prior probability is jointly Gaussian,

$$p(a) = \frac{1}{Z} \exp(-(a - \mu_a)^T \Lambda^{-1} (a - \mu_a)).$$

2. Total observation noise and representation error is Independent Identically Distributed (IID) Gaussian with a diagonal covariance matrix,

$$v^{(i)} = H^{(i)} e_x + n^{(i)}$$

$$\hat{a}^{(i)} = \Psi^T H^{(i)} \Phi a + \Psi^T v^{(i)} \quad (5)$$

$$p(v^{(i)}) = \frac{1}{Z} \exp(-(v^{(i)} - \mu_v^{(i)})^T K^{-1} (v^{(i)} - \mu_v^{(i)})).$$

With these two assumptions, the conditional probability  $p(\hat{a}^{(1)}, \dots, \hat{a}^{(M)} | a)$  can be re-calculated as follows. According to multivariate random variable theory,  $\Psi^T v^{(i)}$  is also a Gaussian distribution,  $p(\Psi^T v^{(i)}) = \frac{1}{Z} \exp(-(\Psi^T v^{(i)} - \Psi^T \mu_v^{(i)})^T Q^{-1} (\Psi^T v^{(i)} - \Psi^T \mu_v^{(i)}))$ , where  $Q = \Psi^T K \Psi$ . Since  $\hat{a}^{(i)} - \Psi^T H^{(i)} \Phi a = \Psi^T v^{(i)}$ , so the individual conditional probability can be shown as,

$$p(a^{(i)} | a) = \frac{1}{Z} \exp(-(\hat{a}^{(i)} - \Psi^T H^{(i)} \Phi a - \Psi^T \mu_v^{(i)})^T Q^{-1} (\hat{a}^{(i)} - \Psi^T H^{(i)} \Phi a - \Psi^T \mu_v^{(i)})).$$

From (5),  $\hat{a}^{(i)} - \Psi^T H^{(i)} \Phi a$  is IID as a consequence of the fact that  $\Psi^T v^{(i)}$  is IID, thus,

$$p(\hat{a}^{(1)}, \dots, \hat{a}^{(M)} | a) = \prod_i p(\hat{a}^{(i)} | a) =$$

$$\frac{1}{Z} \exp(-\sum_{i=1}^M (\hat{a}^{(i)} - \Psi^T H^{(i)} \Phi a - \eta)^T Q^{-1} (\hat{a}^{(i)} - \Psi^T H^{(i)} \Phi a - \eta)).$$

The estimation problem can then be rewritten as,

$$\begin{aligned} \tilde{a} &= \operatorname{argmax}_a p(\hat{a}^{(1)}, \dots, \hat{a}^{(M)} | a) p(a) \\ &= \operatorname{argmax}_a \frac{1}{Z} \exp(-\sum_{i=1}^M (\hat{a}^{(i)} - \Psi^T H^{(i)} \Phi a - \eta)^T Q^{-1} (\hat{a}^{(i)} - \Psi^T H^{(i)} \Phi a - \eta)) \times \frac{1}{Z} \exp(-(a - \mu_a)^T \Lambda^{-1} (a - \mu_a)) \end{aligned}$$

$$= \operatorname{argmin}_a (\sum_{i=1}^M (\hat{a}^{(i)} - \Psi^T H^{(i)} \Phi a - \eta)^T Q^{-1} (\hat{a}^{(i)} - \Psi^T H^{(i)} \Phi a - \eta) + (a - \mu_a)^T \Lambda^{-1} (a - \mu_a)).$$

### Stage 5: Estimating solution by iterative steepest decent

The estimation problem in Stage 4 can be solved by iterative steepest descent,

$$a_n = a_{n-1} + \alpha \nabla E(a_{n-1}), \quad (6)$$

where  $E(a)$  is the cost function, defined as,

$$E(a) = \frac{1 - \lambda}{2} \sum_{i=1}^M (\hat{a}^{(i)} - \Psi^T H^{(i)} \Phi a - \eta)^T Q^{-1} (\hat{a}^{(i)} - \Psi^T H^{(i)} \Phi a - \eta) + \frac{\lambda}{2} (a - \mu_a)^T \Lambda^{-1} (a - \mu_a).$$

By calculating the derivative of  $E(a)$ , and substituting the result back into Equation (6), the iterative solution for estimating a HR feature can be represented as,

$$a_n = a_{n-1} - \alpha \left[ - (1 - \lambda) \sum_{i=1}^M \Psi^T H^{(i)T} \Phi Q^{-1} (\hat{a}^{(i)} - \Psi^T H^{(i)} \Phi a - \eta) + \lambda \Lambda^{-1} (a_{n-1} - \mu_a) \right].$$

## 4. EXPERIMENTS

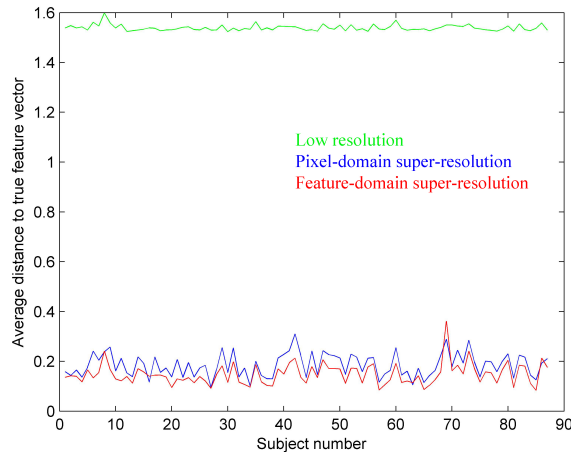
The Multiple Biometric Grand Challenge dataset [10] is organized by the National Institute of Standards and Technology to promote face and iris recognition technology on both still and video imagery. A subset of subjects with high quality still iris images has been selected from the dataset. Two high quality iris images are selected for each subject. One iris image serves as the gallery image, while the other is degraded by Gaussian blurring, random warping and downsampling by a factor of four to create a series of 16 low resolution images.

In pixel-domain super-resolution approaches such as the one described in [7], a HR image is created from one LR iris sequence. This HR image is then encoded to extract the HR features for recognition. In contrast, the proposed feature-domain super-resolution approach extracts features from all LR iris images in the LR sequence, and then super-resolves these features directly to create a HR feature for recognition. The true HR feature for use as ground-truth is calculated by encoding the original high-resolution probe image. To demonstrate the effectiveness of the proposed approach, we compare the average distance of the reconstructed features to the true features and show recognition performance.

### 4.1. Average Distance to true feature vectors

The distance between a reconstructed feature vector,  $\tilde{a}$ , and the true HR feature vector,  $a$ , is calculated for each subject as follows,

$$D(a, \tilde{a}) = \frac{\|a - \tilde{a}\|}{\|a\|} \times \frac{1}{\text{Length}(a)}$$



**Fig. 2.** Average distance to true feature vector.

where  $\|\cdot\|$  is Euclidean distance,  $Length(a)$  - the length of vector  $a$ , is used for normalisation. The distance between a reconstructed HR feature vector using the proposed feature-domain super-resolution approach and the true HR feature vector is compared with the distance between a reconstructed HR feature vector using the pixel-domain super-resolution approach and the true HR feature vector, and the distance between the LR feature and the true HR feature. Figure 2 shows that the proposed feature-domain super-resolution approach achieves closer features to the true features.

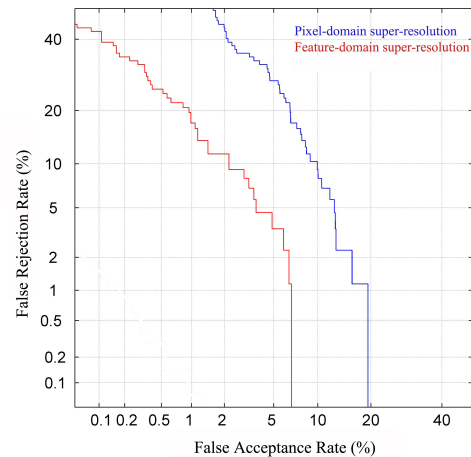
#### 4.2. Recognition performance

Figure 3 illustrates recognition performance of feature-domain super-resolution against pixel-domain super-resolution. The proposed feature-domain approach achieves superior performance by directly super-resolving only information essential for recognition and incorporating iris model constraints.

### 5. CONCLUSION

The use of feature-based super-resolution to improve the performance of iris recognition has hitherto remained unexplored. In this paper we have investigated feature-domain super-resolution for iris recognition using eigeniris as the features. We have shown how these features can be super-resolved directly in the feature domain. In addition, by incorporating specific iris model constraints, recognition performance has been improved when compared to a pixel-based super-resolution system.

It should however be noted that 2D Gabor wavelets are more discriminant features for iris recognition than eigeniris features [1]. Based on the positive initial results outlined in this work, we expect that a feature-domain super-resolution approach using 2D Gabor features will improve iris recogni-



**Fig. 3.** Recognition performance.

tion performance over other pixel-based super-resolution approaches. Our current research is targeted in this direction.

### 6. REFERENCES

- [1] J. Daugman, "How iris recognition works," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 14, pp. 21 – 30, 2004.
- [2] N.D. Kalka, J. Zuo, N.A. Schmid, and B. Cukic, "Estimating and fusing quality factors for iris biometric images," *IEEE Transactions on Systems, Man, and Cybernetics Part A: Systems and Humans*, vol. 40, no. 3, pp. 509 – 524, 2010.
- [3] S.C. Park, M.K. Park, and M.G. Kang, "Super-resolution image reconstruction: a technical overview," *IEEE Signal Processing Magazine*, vol. 20, no. 3, pp. 21 – 36, 2003.
- [4] F. Lin, C. Fookes, V. Chandran, and S. Sridharan, "Super-resolved faces for improved face recognition from surveillance video," in *Lecture Notes in Computer Science*, Seoul, Korea, Republic of, 2007, vol. 4642 LNCS, pp. 1 – 10.
- [5] Kwang Y.S., Kang R.P., Byung J.K., and Sung J.P., "Super-resolution method based on multiple multi-layer perceptrons for iris recognition," in *Ubiquitous Information Technologies Applications, ICUT '09. International Conference on*, 20-22 2009, pp. 1 – 5.
- [6] G. Fahmy, "Super-resolution construction of iris images from a visual low resolution face video," in *Signal Processing and Its Applications, ISSPA 2007. 9th International Symposium on*, 12-15 2007, pp. 1 – 4.
- [7] K. Nguyen, C. Fookes, S. Sridharan, and S. Denman, "Focus-score weighted super-resolution for uncooperative iris recognition at a distance and on the move," *25th International Conference of Image and Vision Computing New Zealand, IVCNZ*, 2010.
- [8] B.K. Gunturk, A.U. Batur, Y. Altunbasak, M.H. Hayes, and R.M. Mersereau, "Eigenface-domain super-resolution for face recognition," *Image Processing, IEEE Transactions on*, vol. 12, no. 5, pp. 597 – 606, 2003.
- [9] M.A. Turk and A.P. Pentland, "Face recognition using eigenfaces," *Proceedings 1991 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 586 – 91, 1991.
- [10] P.J. Phillips, P.J. Flynn, J.R. Beveridge, W.T. Scruggs, A.J. O'Toole, D. Bolme, K.W. Bowyer, B.A. Draper, G.H. Givens, Yui Man Lui, H. Sahibzada, III Scallan, J.A., and S. Weimer, "Overview of the multiple biometrics grand challenge," in *Advances in Biometrics. Proceedings Third International Conference, ICB 2009*, Berlin, Germany, 2009, pp. 705 – 14.